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THE MODELED CEILING AND VISIBILITY (MODCV) PROGRAM

by

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JANUARY 1989

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19. Abstract: Describes USAFETAC's Modeled Ceiling and Visibility (MODCV) computer program. Explains how cumulative distributions of ceiling and visibility are modeled with Weibull and reverse Weibull curves, which are used to produce unconditional probabilities and, with an Orstein-Uhlenbeck process, conditional climatologies for ceiling, visibility, and joint ceiling and visibility. Output is in tabular format by category and time lag. Keywords:

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PREFACE

The MODCV (Modeled Ceiling and Visibility) program was developed by the United States Air Force Environmental Technical Applications Center's Environmental Simulation Branch (USAFETAC/DNY) for Air Weather Service's Central Support Division (AWS/DOOX) after Air Weather Service asked for a computer model that would help meet the climatological database needs of AWS field units by making ceiling and visibility climatology available from a microcomputer. Probability tables produced by MODCV can be used in the field to forecast ceiling and visibility categories.

The main purpose of this technical note is to familiarize AWS analysts and forecasters with how the MODCV program works by describing the algorithms that generate the conditional and unconditional probability tables for cloud ceilings and visibilities.

Original MODCV algorithms were developed by Mr. Albert R. Boehm in 1975. Capt Robert LaFebre later expanded Boehm's work to include conditional and unconditional climatology for ceiling, visibility, and joint ceiling-visibility.

For more information on ceiling and visibility modeling, see Chapter 3, USAFETAC/TN-82/004, *Basic Techniques in Environmental Simulation*; Chapter 2; USAFETAC/TN-83/003, *Ceiling/Visibility Simulation Model;* and Chapters 1-4, AWS-TR-75-259, *Transormalized Regression Probability.*

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Chapter 1

INTRODUCTION TO MODCV

1.1 **Description.** MODCV (Modeled Ceiling and Visibility) uses probabilities derived from cumulative frequency distributions to produce conditional and unconditional probabilities of ceiling, visibility, and joint ceiling and visibility. MODCV calculates probabilities for a given location by using modeling coefficients specifically determined from climatological data for that location. Eight sets of modeling coefficients that span 3-hour time blocks are generated for each month.

1.2 **Requirement and Development.** Climatology requirements of the typical base weather station have, up to now, been satisfied by Revised Uniform Standard Surface Weather Observations (RUSSWO), Wind Stratified Conditional Climatology (WSCC) tables, and AWS Climatic Briefs. But the recent addition of the microcomputer to most AWS stations provided for the possibility of letting forecasters complement those printed summaries with climatology databases stored in their computers.

In 1985, therefore, USAFETAC's Operating Location A at Asheville, NC, was asked to prepare cost estimates for transferring a climatological database package to floppy disks--a package that could be used on the Zenith Z-100 microcomputers with which most AWS weather stations were equipped. Unfortunately, OL-A found that it took at least 31 diskettes per station to store its RUSSWO (4 diskettes), WSCC tables (24 diskettes), Climatic Brief (1 diskette), and Temperature-Dewpoint (TT/TD) curves (4 diskettes). The sheer size and extent of the disk library so created made microcomputer climatology a cumbersome and impractical undertaking, at least for the time being.

Then in April 1986, AWS/DOOX asked USAFETAC to develop a modeled climatology that would be capable of producing unconditional and conditional probabilities for ceiling, visibility, and joint ceiling and visibility. That request was the basis for an extended USAFETAC project, probably to span a number of years, that will eventually develop a comprehensive modeled climatology of all sensible weather elements. The results of ceiling and visibility modeling efforts to date are described in the following chapters.

Chapter 2

MODCV METHODOLOGY

2.1 Unconditional Probability. Unconditional climatology data is easily tabulated at any location for which a representative period of record is available. Unconditional probability is based on the calculation of the relative frequency at which a certain condition occurs. For example, the unconditional probability of ceiling below 3,000 feet at 00Z is found by dividing the number of 00Z observations with ceilings below 3,000 feet by the total number of 00Z observations. This process is what we call the "tabular" approach to calculating frequency distributions; RUSSWO ceiling and visibility climatology is an example of data produced with this method.

A flexible and extremely powerful alternative to the tabular approach is to model the "cumulative distribution function," or CDF, with a mathematical function. In other words, we use a mathematical equation to fit the curve associated with the CDF. As a result, the cumulative probability associated with any value of the continuous variable of interest can be derived from the equation:

$$P = F(x) \tag{2.1}$$

where *F(x)* is the function that simulates the curve of the CDF. Given any threshold value of the variable x, therefore, we can calculate the unconditional probability that x will be below that threshold value. MODCV uses this modeled distribution technique to produce unconditional ceiling and visibility probabilities. An expanded discussion of fitting curves to the CDFs is given in section 3.2, Model Input.

2.2 Conditional Probability. The basic component of USAFETAC's *conditional ceiling and visibility probability* model is based on the Ornstein-Uhlenbeck (O-U) stochastic (random) process, a first-order Markov process for which each value of a random variable y_t is considered a particular value of a stationary stochastic process. The stochastic model relates a value of y, at time t (y_t), to an earlier initial value of y at time zero (y_0).

A frequent assumption in statistical application is that the variable being analyzed is normally distributed. Unfortunately, many meteorological variables (including ceiling and visibility) are *not* normally distributed. However, variables can be transformed into a normal distribution by expressing the raw variable in terms of its "equivalent normal deviate," or END. This process, known as "transnormalization," is discussed by Boehm (1976) and is summarized in Paragraph 2.3. Once the variables have been normalized, the joint density function associated with the two variables y_0 and y_t becomes:

$$f(y_0, y_t) = \frac{1}{2\pi\sigma^2\sqrt{(1-\rho^2)}}\, exp\left[\frac{(y_0-\mu)^2 - 2\rho(y_0-\mu)(y_t-\mu) + (y_t-\mu)^2}{2\sigma^2(1-\rho^2)}\right] \tag{2.2}$$

where ρ is the serial correlation between successive values of y and where μ and σ represent the mean and standard deviation of y, respectively. Since we are interested in the conditional probability of y_t given the initial value of y_0, a conditional distribution of the weather variables is required. If the weather process can be approximated by a first-order Markov equation, then the value of y_t is dependent only upon the value of y_0. If successive observations of y have a bivariate normal distribution, the conditional distribution of y_t is normal with a mean of:

$$E[(y_t|y_0)] = \sigma + \rho(y_0 - \mu) \tag{2.3}$$

and a variance of:

$$var\left[(y_t|y_0) = \sigma^2(1-\rho^2)\right] \tag{2.4}$$

Equations 2.3 and 2.4 are basic to the first-order Markov equation. Specifically, a value of the variable y_t can be calculated, using:

$$y_t = \mu + \rho(y_0 - \mu) + \sigma\sqrt{1-\rho^2}\,\eta_t \tag{2.5}$$

If the variable of interest is distributed normally with a mean of zero and a variance of one, N(0,1), then equation 2.5 reduces to:

$$y_t = \rho y_0 + \sqrt{(1-\rho^2)}\,\eta_t \tag{2.6}$$

where ρ is the correlation coefficient between y_0 *and* y_t separated by a time interval t (hours), and where η_t is a random normal number. The process is considered Markov if $\rho = \rho_0{}^t$, where ρ_0 is the hour-to-hour correlation associated with y. If ρ_0 is a constant, then this process is considered stationary and is known as the "*Ornstein-Uhlenbeck*" (or O-U) process.

Application of the O-U process to meteorological variables is well documented in the literature (Gringorten, 1966; Sharon, 1967; Gringorten, 1971; Whiton and Berecek, 1982). Its application to variables whose time series has a random component and which adhere to the restrictions of the Markov process is justifiable. "Stationarity" is a characteristic that is especially favorable for application to weather variables since predictions derived from stationary processes will converge to the mean value of the variable y as the time t increases. That is, prediction from the O-U process will converge toward unconditional climatological values as the forecast time period increases.

From equation 2.6 we can conclude that, for a specific value of y_0, the value of η_t will exceed a minimum value η_{min} as frequently as y_t exceeds a minimum value y_{min}, given an initial value y_0. In terms of probability,

$$P(\eta_t \geq \eta_{min}) = P(y_t > y_{min}|y_0) \tag{2.7}$$

Now we can replace the value of η_t as $y(t|0)$, the normalized value corresponding to the conditional probability of y_t. Using basic algebra, we can rewrite equation 2.6 as:

$$P(Y_t|Y_0) = P(y_t > y_{min}|y_0) \tag{2.8}$$

where $P(y_t|y_0)$ is the conditional probability of y_t given the value of y_0, $P(y_t)$ is the unconditional probability of y at time t, and $P(y_0)$ is the unconditional probability of y at time zero. MODCV uses equation 2.8 to calculate conditional probabilities of ceiling and visibility. It should be clear by now that the conditional probability of y_t is a direct function of the unconditional probability of y_t and y_0. MODCV uses the modeled unconditional probabilities discussed in Paragraph 2.2, "Unconditional Probability," as input to the conditional probability equations.

2.3. Transnormalization. Although the O-U process doesn't require that the variable y_t be normally distributed, equation 2.6 is derived by assuming that it is distributed N(0,1). Since most weather variables are *not* normally *distributed, a transformation* to a normal distribution is required. This process is referred to as "*transnormalization*."

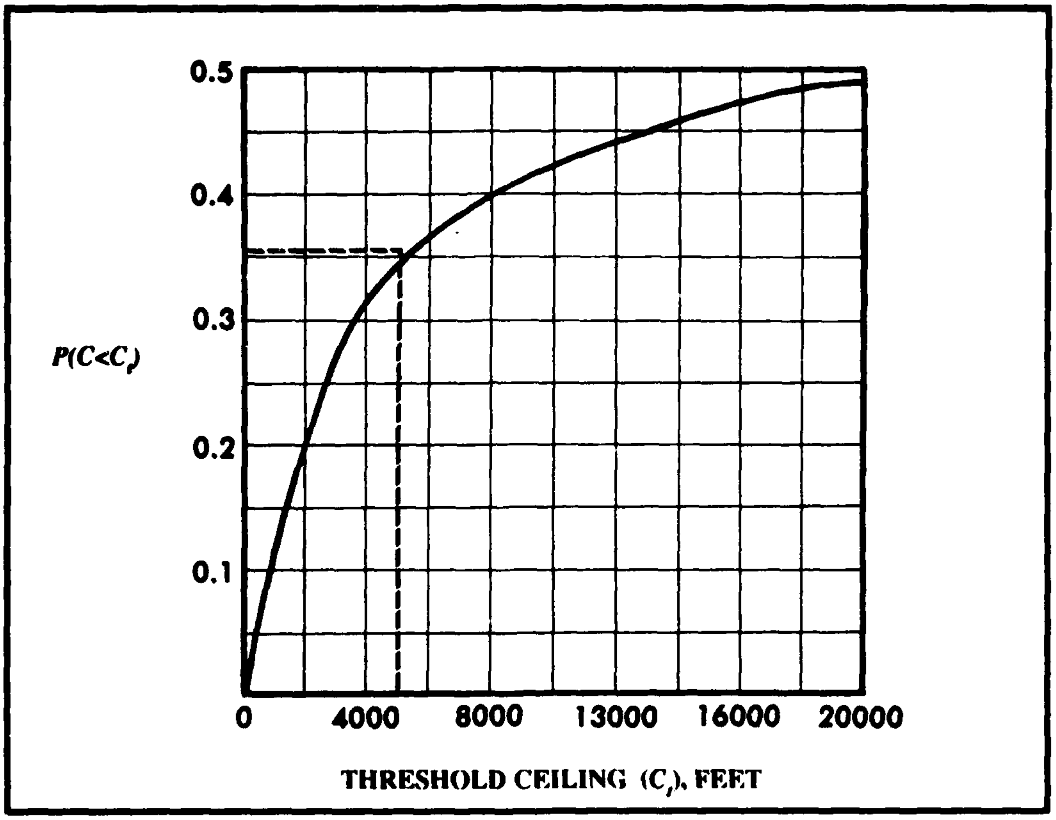

Figure 2.1. Cumulative Distribution Function (CDF) of the Ceiling at Loring AFB, ME, for January at 1200 LST. The CDF is extracted from the Loring AFB RUSSWO.

Figure 2.1 shows an empirical cumulative distribution function (CDF) for ceiling height. It is is simply a graph of threshold ceiling heights (C_t) versus the cumulative probability (P) of a ceiling height less than a given threshold value. The dashed lines identify the cumulative probability that a ceiling height (C) is less than a threshold value (C_t) of 5,000 feet. The probability that C is less than C_t = 5,000 ft is 0.351; that is, $P(C < C_t) = 0.351$. In the context of the standard normal density function, $P(C<C_t)$ corresponds to some END represented by $\check{c}$. In other words, the integral of the standard normal density function $f(z)$ from $z = -\infty$ to $z = \check{c}$ is equal to $P(C<C_t)$ where

$$f(z) = \frac{1}{\sqrt{2\pi}} \, exp - (z^2/2) \qquad (2.9)$$

and

$$f(C_t) = P(C<C_t) = \int_{-\infty}^{\check{c}} f(z)\,dz \qquad (2.10)$$

The probability $P(C<C_t)$ represents the area under the standard normal curve as shown in Figure 2.2. For this example, the END associated with $P(C<C_t) = 0.351$ is $\check{c} = -0.381$.

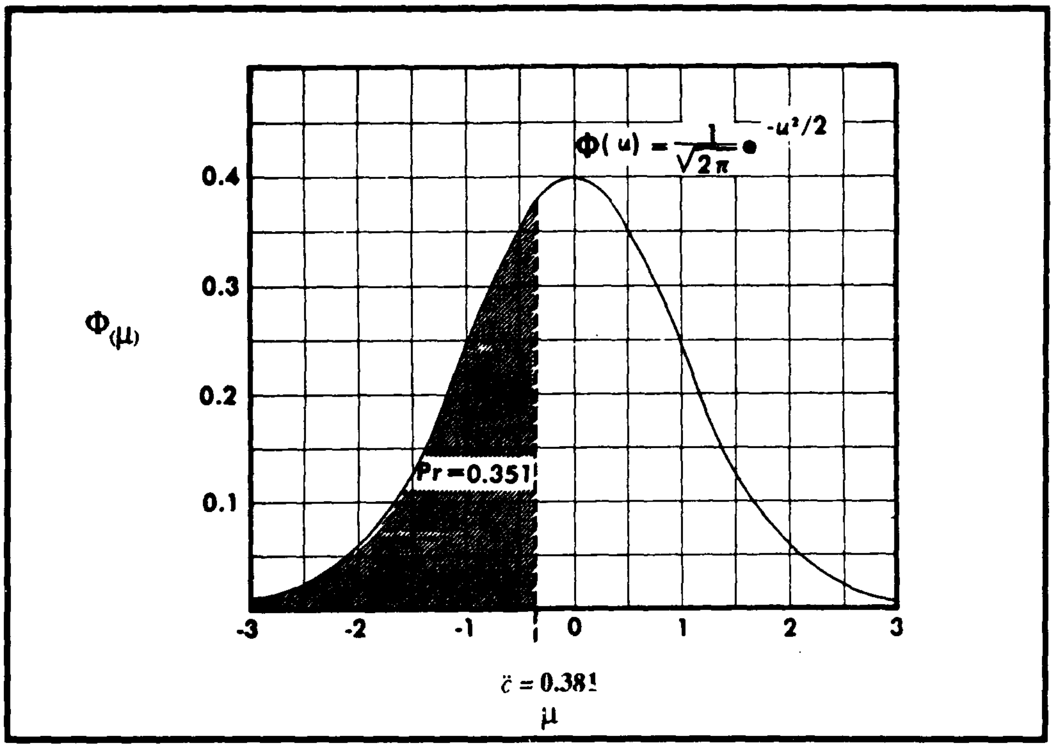

Figure 2.2. Normal Probability Distribution. Integrated from -∞ to $\ddot{c}$ = -0.381, it yields a cumulative probability (P) of 0.351.

Using the transnormalization process, the probability of a ceiling height less than some threshold corresponds to a specific END that is based on the empirical CDF of ceiling heights. Since ENDs are distributed N(0,1), they can be used as variables in the O-U process, where equation 2.8 becomes

$$P(C_t|C_0) = \frac{\ddot{c}_t - \rho\ddot{c}_0}{\sqrt{1-\rho^2}} \tag{2.11}$$

where $\ddot{c}$ values are ENDs of the ceiling C.

2.4 An Application of the O-U Process. To understand how these processes work together to estimate a conditional probability, consider a case in which the initial ceiling height is 2,000 feet. In Table 2.1, $P(C<2{,}000$ feet) = .203 and corresponds to an END of $\ddot{c}_o$ = -0.833. If we assume a serial correlation of ρ = 0.95, we can estimate the probability of a ceiling height less than or equal to a specific value at some time, t, in the future. For example, suppose we want to know what the probability is that the ceiling 1 hour later is less than 1,000 feet. In Table 2.1, $P(C_t<1{,}000$ ft) = 0.113 which yields an END of $\ddot{c}_t$ = -1.209. Using equation 11, we see that

$$P(C_t|C_0) = \frac{-1.209 - (0.95)(-0.833)}{\sqrt{1-(0.95)^2}} = -1.338 \tag{2.12}$$

The value of -1.338 is the END of the probability value of the ceiling being less than 1,000 feet, given that the initial ceiling height was 2,000 feet. The END of -1.338 corresponds to a $P(C|C_i)$ = 0.090. Therefore, there is a 9.0% chance that the ceiling will fall to less than 1,000 feet within 1 hour, given that the initial ceiling was 2,000 feet.

TABLE 2.1. Transnormalization from Ceiling to END for Loring AFB, ME, January, 1200 LST.

Ceiling (feet)	Cumulative Probability ($C<C_t$)	END
0	0.000	$-\infty$
200	0.009	-2.295
1,000	0.113	-1.209
2,000	0.203	-0.833
5,000	0.269	-0.612
10,000	0.351	-0.381
20,000	0.489	-0.032

2.5 Expanding the Conditional Probability Model to Two Variables. The conditional probability model shown in equation 2.6 can only be applied to a time series of a single variable, such as ceiling. But in meteorology, we are frequently concerned with threshold values of two interrelated variables, such as ceiling and visibility, and we are interested in the probability that one or both will be below certain thresholds. With MODCV, we can calculate the conditional and unconditional probabilities given joint threshold values of ceiling and visibility. The probability of these joint conditions is obtained in two steps. First, individual conditional probabilities are calculated for the ceiling and visibility thresholds using:

$$\ddot{P}(C_t|C_0) = \frac{\ddot{c}_t - \rho_c \ddot{c}_0}{\sqrt{1-\rho_c^2}} \tag{2.13}$$

$$\ddot{P}(V_t|V_0) = \frac{\ddot{v}_t - \rho_v \ddot{v}_0}{\sqrt{1-\rho_v^2}} \tag{2.14}$$

where C_t/V_t is ceiling/visibility at time t and C_0/V_0 is ceiling/visibility at the initial time. The ENDs of the conditional probabilities ($\ddot{P}$) are converted back to conditional probabilities of a ceiling or visibility below the threshold. Next, we subtract this conditional probability from one to obtain the probability of a ceiling or visibility at or above the threshold, as shown below.

$$P(C_{at}|C_0) = 1 - P(C_t|C_0) \qquad and \qquad P(V_{at}|V_0) = 1 - P(V_t|V_0) \tag{2.15}$$

where C_{at}/V_{at} represent a ceiling/visibility at or above the threshold. The joint conditional probability of both ceiling and visibility being at or above their respective thresholds is obtained by:

$$P(C_{at}, V_{at}|C_0, V_0) = 0.7P(C_{at}|C_0)\ P(V_{at}|V_0) + 0.3MIN\,[P(C_{at}|C_0), P(V_{at}|V_0)] \tag{2.16}$$

By subtracting the result of Equation 2.16 from one, we now have the probability of a ceiling being below a threshold, visibility being below a threshold, or both being below a threshold. Equation 2.16 incorporates a unique application of the independence characteristic associated with the probability of two events. If two events are completely independent, then the joint probability is simply the probability of the first event multiplied by the probability of the second. If the events are completely dependent, however, then the probability of either event or of a combined event is just the maximum of the two individual probabilities. Equation 2.16 is a weighted combination of these probability concepts developed by Boehm (1977).

Chapter 3

MODCV ASSUMPTIONS AND LIMITATIONS

3.1 **Basic Mathematical Assumptions.** As with all deterministic or statistical models, simplifying assumptions must be made. These assumptions impose limits on the model's ability to provide sound guidance. Knowledge of these limitations is important to using this model as a forecasting tool. MODCV tries to optimize speed and accuracy while trying to minimize the need to process large amounts of data.

3.2 **Modeling Cumulative Distributions with Weibull Curves.** A fundamental assumption of this model is that the Weibull and Reverse Weibull curves adequately describe the cumulative probability distributions of ceiling and visibility. A measure of closeness of fit is the root mean square (RMS) difference between the observed and modeled distributions. RMS differences vary by hour, month, and station, depending on the characteristics of the observed distribution. However, unconditional probabilities can usually be fit by Weibull curves with an RMS difference of 3-6 percent, an accuracy that is usually within tolerance for most users.

3.3 **Temporal Spreading of Modeled Cumulative Distributions.** MODCV is designed to provide probability information for any hour of any month. To save computer space and time, modeled cumulative distribution curves were compiled for 3-hour time periods centered on 00Z, 03Z, 06Z, 09Z, 12Z, 15Z, 18Z, and 21Z. This was accomplished by including all hourly observations in that 3-hour time period into the empirical distribution. The assumption is made that the modeled distribution is valid for any hour within the 3-hour time period.

3.4 **Inverse Transnormalization.** MODCV inputs ENDs of the cumulative probability for ceiling or visibility into Equation 2.11. Although the O-U process does not require that the random variable y_t is normally distributed, the inverse transnormalization process does. Inverse transnormalization is the process that converts the END of the *conditional* probability $\hat{P}(y_t|y_0)$ back to an *actual* probability value $P(y_t|y_0)$. This process is equivalent to integrating the normal density function from minus infinity to the END value of the conditional probability.

The inverse transnormalization process will produce consistently accurate probabilities if the END values are distributed N(0,1). Therefore, MODCV assumes that the END of the conditional probability produced by the O-U process is distributed N(0,1). This assumption was painstakingly tested by Bereeck (1983). Using Chi-Square tests and tests for skewness, it was shown that the O-U process consistently produces ENDs of conditional probabilities that are distributed N(0,1).

3.5 **Serial Correlation.** The O-U process requires a serial correlation (ρ) as an input to calculate conditional probabilities. The correlation values used in this model are 0.95 for ceiling and 0.94 for visibility. They represent the END correlation between hour-to-hour observations of these variables. It should be evident that hourly correlations of ceiling and visibility will vary depending on climate, station, and season. MODCV assumes that these values are representative for all locations and that any difference from actual station correlation is negligible.

Chapter 4

MODCV INPUT AND OUTPUT

4.1 **Observational Input Limitations.** MODCV produces probabilities of ceiling and visibility that are consistent in time and representative of a given location. The term "consistent" indicates that the serial correlations of ceiling and visibility are preserved in a way that conforms with patterns actually observed in nature. Maintaining serial correlations requires that the "past weather" at a given location must be analyzed to obtain the appropriate probability distributions. USAFETAC has the resources necessary to provide this type of analysis because its mission includes permanent archival of all weather observations collected by the USAF automated weather network (AWN). The quality of the observational data collected and archived, however,varies by location. Stations in western industrialized nations generally follow WMO procedures and report on a regular schedule. Data from other locations, particularly those in the Third World, do not always observe WMO standards nor adhere to synoptic schedules. Data coverage in the latter regions is often sparse, as well. Poor data quality input naturally affects USAFETAC's ability to use MODCV to its full potential for every location in the world.

4.2 **Data Input Requirements** consist of modeling coefficients for each location for which probabilities are to be calculated. There are two sets of coefficients: one for ceiling and one for visibility, as shown in Table 4.1. Each set consists of 96 pairs of coefficients representing each of the eight time blocks that were discussed in Paragraph 3.3 for each of the 12 months.

TABLE 4.1. Weibull and Reverse Weibull Function Modeling Coefficients for January at Scott AFB, Illinois.

	Weibull		*Reverse Weibull*	
Time (GMT)	α	ß	α	ß
0000	0.072964	1.076343	35.052795	-0.439868
0300	0.068906	1.105603	35.952148	-0.432142
0600	0.060347	1.103759	35.766785	-0.433737
0900	0.064854	1.118966	39.929581	-0.457944
1200	0.083187	1.082496	37.909668	-0.459744
1500	0.100389	1.081702	38.308655	-0.468665
1800	0.080195	1.076881	40.062897	-0.465425
2100	0.102712	0.914098	40.241989	-0.465896

4.3 **Modeling Coefficients.** A computer tape of weather data for a typical location contains weather observations for a certain period of record, usually 10 years or more. These data are stratified by month and time of day. Threshold values are used to define categories of ceilings and visibilities (see Figure 4.1 for Sembach AB, West Germany). Frequency values associated with these categories are tabulated and used to construct the empirical CDF. The cumulative probabilities that the ceiling and visibility are less than selected thresholds are calculated from the historical weather records for each month at the eight 3-hour time periods. The empirical CDF is used in a linear regression technique to develop a set of coefficients for a mathematical function that fit a theoretical distribution. This distribution-fitting procedure is a fundamental concept that provides geographical realism for the model. Diurnal, seasonal, and local variations in visibility and ceiling at each location are represented in the variability of these modeling coefficients.

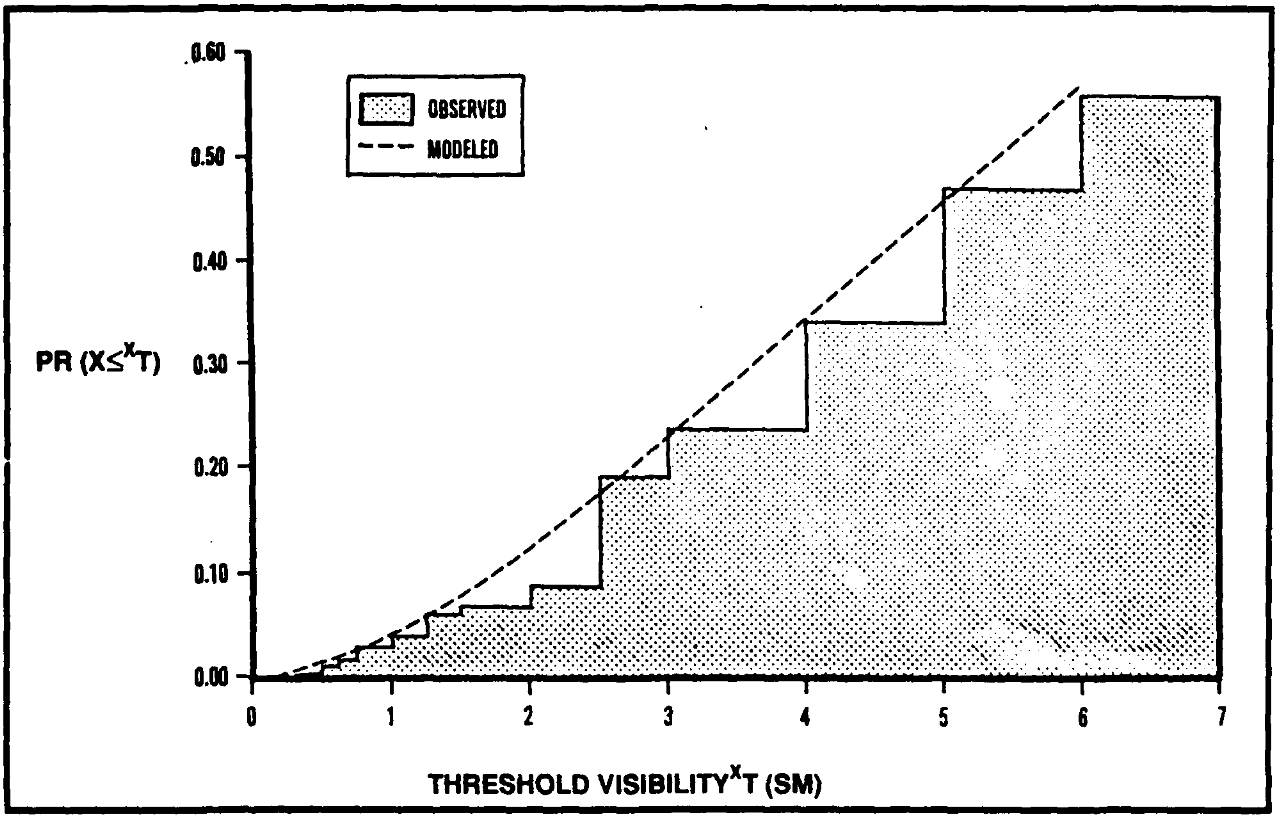

Figure 4.1. Observed and Modeled CDFs for Visibility at Sembach AB, January, 2300-0100Z.

4.4 Deriving Coefficients for Visibility. USAFETAC's basic modeling equation for the CDF of visibility is the Weibull curve. Use of the Weibull curve for modeling visibility is well documented by Somerville, Bean, and Falls (1979); Somerville and Bean (1981); and Whiton and Berecek (1982). The Weibull curve is expressed by the equation:

$$P = 1 - exp\left(-\alpha X_t^{\beta}\right) \tag{4.1}$$

where α and β are the modeling coefficients, X_t is some threshold visibility in statute miles, and P is the probability that an actual visibility observation (X) will be less than X_t. In earlier applications of the Weibull distribution, estimates of α and β were obtained through an iterative solution of the maximum likelihood equations. USAFETAC uses a different approach, in which values of the empirical cumulative distribution are regressed on the Weibull distribution function. The calculated coefficients minimize the difference between the empirical and theoretical cumulative distributions; this is advantageous because the objective is to reproduce the empirical distribution and not estimate α and β for their own sakes. The technique is as follows:

(1) Let $Q = 1-P$ (the probability that X is greater than X_t) and substitute into Equation 4.1.

$$Q = exp\,(-\alpha X_t^{\beta}) \tag{4.2}$$

(2) Take the natural logarithm of each side of Equation 4.2.

$$lnQ = -\alpha X_t^{\beta} \tag{4.3}$$

(3) Multiply each side of Equation 4.3 by minus one; once again, take the natural logarithm of each side.

$$ln(-lnQ) = ln\alpha + \beta lnX_t \tag{4.4}$$

(4) Estimates of α and ß are obtained by fitting a straight line to the set of ordered pairs of lnX_t and $ln(-lnQ)$ by a least squares technique. Using this data and the normal equations for a straight line, the solution for ß is:

$$ß = \frac{n\Sigma(\ln X_t)(\ln(-\ln Q)) - (\Sigma \ln X_t)(\Sigma \ln(-\ln Q))}{n\Sigma \ln X_t^{\,2} - (\Sigma \ln X_t)^2} \tag{4.5}$$

and the solution for α is

$$\alpha = exp\,\overline{(\ln(-\ln Q))} - ß\overline{X_t} \tag{4.6}$$

(5) For successful application of this technique, Q must be greater than zero but less than one, since $ln(-lnQ)$ will be defined for those values. One problem does result from this technique: although the root mean square error (RMSE) is minimized in $ln(-lnQ)$ space, the RMSE is not necessarily minimized in Q space. A weighting factor (WF) is necessary to minimize the RMSE; the resulting equations for α and ß are:

$$ß = \frac{\Sigma WF\Sigma(\ln X_t)(\ln(-\ln Q))(WF) - (\Sigma WF \ln X_t)(\Sigma WF \ln(-\ln Q))}{(\Sigma WF \Sigma WF \ln X_t^2) - (\Sigma WF \ln X_t)^2} \tag{4.7}$$

$$\alpha = exp\left(\frac{\Sigma WF \ln(-\ln Q)}{\Sigma WF} - ß\frac{\Sigma WF \ln X_t}{\Sigma WF}\right) \tag{4.8}$$

where:
$$WF = (QlnQ)^2 \tag{4.9}$$

4.5 Deriving Coefficients for Ceiling. USAFETAC uses a slightly different version of the Weibull curve (called the "Reverse Weibull") to fit ceiling data to a cumulative distribution. The Reverse Weibull curve is given by:

$$P = exp(-\alpha X_t^{ß}) \tag{4.10}$$

where α and ß are modeling coefficients determined from the empirical distributions, X_t is some threshold value of ceiling in feet, and P is the probability that an actual ceiling observation (X) is less than X_t. The technique used to solve for α and ß is similar to that used and shown earlier. A straight line is fit to the ordered pairs of the data ln X_t and $ln(-lnP)$ using the normal equations. Again, a weighting factor (WF) is applied to minimize the RMSE in P space. The resulting equations for α and ß are:

$$ß = \frac{\Sigma WF\Sigma(\ln X_t)(\ln(-\ln P))(WF) - (WF \ln X_t)(WF \ln(-\ln P))}{(\Sigma WF)(\Sigma WF \ln X_t^2) - (\Sigma WF \ln X_t^2)} \tag{4.11}$$

$$\alpha = exp\left(\frac{\Sigma WF \ln(-\ln P)}{\Sigma WF} - ß\,\frac{\Sigma WF \ln X_t}{\Sigma WF}\right) \tag{4.12}$$

where:
$$WF = (PlnP)^2 \tag{4.13}$$

4.6 An Example of Fitting the Cumulative Distribution Function. The first step in the process of fitting a curve to a cumulative distribution (CDF) is to select a series of threshold values for the variable of interest--Table 4.2 lists a series of such threshold values(X_t) for visibility.

TABLE 4.2. Empirical and Modeled Cumulative Probabilities that the Visibility Was Less Than Selected Threshold Values for Sembach AB, January, 2300-0100Z.

Threshold Visibility x_t	*Observed Visibility* $P(X \leq x_t)$	*Modeled Visibility* $P(X \leq x_t)$	*Residual*
0.025	0.000	0.004	-0.004
0.313	0.004	0.006	-0.002
0.500	0.011	0.013	-0.002
0.625	0.018	0.019	-0.001
0.750	0.029	0.025	0.004
1.000	0.040	0.040	0.000
1.250	0.061	0.058	0.003
1.500	0.068	0.078	-0.010
2.000	0.086	0.123	-0.037
2,500	0.189	0.174	0.015
3.000	0.235	0.229	0.006
4,000	0.339	0.343	-0.004
5.000	0.467	0.458	0.009
6,000	0.556	0.564	-0.008

The next step is to calculate the observed frequency of visibility below that threshold value ($P(X<X_t)$) for a given month and time. Using equations 4.7 and 4.8, coefficients α and β (which fit a specific Weibull curve to the observed distribution) are calculated. Table 4.2 lists these observed and modeled frequencies for Sembach AFB, West Germany, for January between 2300 and 0100 GMT. The α and β values that produce the modeled frequencies are $\alpha = 0.041413$ and $\beta = 1.672692$. In this example, the modeled distribution fits the observed distribution very well. The RMS of the fit was 0.012 and the maximum absolute difference between two curves at any one threshold value was 0.037. Figure 4.1 (on page 9) shows how the Weibull curve fits the observed distribution; fitting a curve to the observed frequency of ceilings is done in much the same way. After selecting threshold ceiling values, the observed distribution is calculated. Then coefficients α and β are calculated with Equations 4.11 and 4.12. Finally, a specific Reverse Weibull curve is fit to the observed ceiling distribution for a given month and hour.

4.7 An Example of Calculating Single-Event Unconditional Probability. Table 4.1 (on page 8) contains all α and β coefficients for the Weibull and Reverse Weibull functions for January at Scott AFB, IL. To compute an unconditional probability of a single event, we simply enter the value of interest into the appropriate equation using the α and β values. For example, we may want to determine the unconditional probability of a ceiling less than 4,000 feet at 0600Z at Scott AFB in January. The Reverse Weibull function is used to model the ceiling distribution; α and β for 0600Z in January are 35.766785 and -0.433737. Using Equation 4.10 and a value of X_t = 4,000 feet,

$$P(C<C_t) = exp\left(-\alpha X_t^{\beta}\right) \tag{4.10}$$

$$P(C<4000\ ft) = exp\left[-35.766787(4000)^{-0.433737}\right]$$

$$P(C<4000\ ft) = 0.375$$

we determine that the unconditional probability of a Scott AFB ceiling less than 4,000 feet at 0600Z in January is 0.375, or 37.5%. The same process is used to calculate unconditional probabilities of visibility, using Weibull function coefficients and Equation 4.1.

4.8 An Example of Calculating Joint-Event Unconditional Probability. Paragraph 2.5 discussed the two-step process required to calculate joint probabilities. In this example, we want to determine the unconditional probability of ceiling less than 3,000 feet and/or visibility less than 3 miles at 0600Z in January at Scott AFB. The first step is to calculate the single event probabilities. For ceiling, $\alpha = 35.766785$ and β -0.433737. Using Equation 4.10 again, we find that the unconditional probability of ceiling less than 3,000 feet is 0.329.

$$P(C<C_t) = exp\left(-\alpha X_t^{\beta}\right) \tag{4.10}$$

$$P(C<3000\ ft) = exp\left[-35.766787(3000)^{-0.433737}\right]$$

$$P(C<3000\ ft) = 0.329$$

For visibility, $\alpha = 0.060347$ and $\beta = 1.103759$. Using Equation 4.10 once more, we find that the unconditional probability of visibility less than 3 miles is 0.184.

$$P(V<V_t) = 1 - exp\left(-\alpha X_t^{\beta}\right) \tag{4.1}$$

$$P(V<3\ miles) = 1 - exp\left[-0.60347(3)^{1.103759}\right]$$

$$P(V<3\ miles) = 0.184$$

The probabilities *above* the threshold, therefore, are 0.671 for ceiling and 0.816 for visibility. The joint probability of these two single events is calculated by using Equation 2.16 and the unconditional probabilities above the thresholds. The joint probability of ceiling less than 3,000 feet and/or visibility less than 3 miles [$P(C<3000\ ft$ *and/or* $V<3\ miles)$] is 0.416 or 41.6%.

$$P(C\geq 3000\ ft, V\geq 3\ miles) = 0.7P(C\geq 3000\ ft)\,P(V\geq 3\ miles) + 0.3MIN\left[P(C\geq 3000\ ft), P(V\geq 3\ miles)\right] \tag{2.16}$$

$$P(C\geq 3000\ ft, V\geq 3\ miles) = 0.7(0.671)(0.816) + 0.3(0.617) = 0.584$$

$$P(C<3000\ ft\ and/or\ 3\ miles) = 1 - 0.584 = 0.416$$

4.9 An Example of Calculating Single-Event Conditional Probability. To estimate the conditional probability of an event, we need the initial condition and the threshold condition at time t. For example, say that the Scott AFB ceiling is 3,000 feet in January at 0600Z, and that we want to know the conditional probability of a ceiling less than 2,000 feet at 1200Z. The first step is to calculate the unconditional probabilities associated with the initial condition and the threshold value at time t. The unconditional probability of a ceiling less than 3,000 feet at 0600 GMT was calculated in the preceding paragraph as 0.329. The unconditional probability of a ceiling less than 2,000 feet at 1200Z is then calculated to be 0.316, as shown below:

$$P(C<2000\ ft) = exp\left[-37.909668(2000)^{-0.459744}\right]$$

$$P(C<2000\ ft) = 0.316$$

The second step is to transnormalize the probabilities of these events (using the transnormalization process discussed in paragraph 2.3) to convert the probability to an END. We do this by using Equation 4.12, in which P is the unconditional probability and $\mathfrak{p}$ is its END.

$$\hat{p} = 4.91[p^{0.14} - (1-p)^{0.14}] \tag{4.14}$$

$$\hat{p}\,(C<3000\ ft) = 4.91[0.329^{0.14} - (1-0.329)^{0.14}]$$

$$\hat{p}(C<3000\ ft) = -0.441$$

The END of the probability of a ceiling less than or equal to 3,000 feet at 0600Z, therefore, is -0.441. Using the same process, the END of the probability of a ceiling less than 2,000 feet at 1200Z would be -0.477.

The third step uses the END values and the Ornstein-Uhlenbeck equation (Equation 2.6), where

$$\hat{p}(y_0) = -0.441 \qquad and \qquad \hat{p}(y_t) = -.477.$$

This process yields the END of the conditional probability ($\hat{p}(y_t|y_0)$), where t = 6 hours, and $p = p_0{}^t$ where p_0 = 0.95. The value of the conditional probability of y_6 = 2,000 feet, given y_0 = 3,000 feet, is -0.489.

$$\hat{p}(y_6 = 2000\ ft|y_0 = 3000\ ft) = \frac{(-0.477)-(0.95)^6(-0.441)}{\sqrt{1-(0.95)^2}} = -0.489$$

The final step is to convert the END of the conditional probability to an actual probability value. This process, known as "inverse transnormalization," can be accomplished mathematically using Equation 4.15.

$$P = \frac{1}{\{1 + exp[-\hat{p}(0.07\hat{p}^2 + 1.6)]\}} \tag{4.15}$$

Inserting the END of the conditional probability into Equation 4.13 yields P = 0.312. In other words, given an initial 3,000 foot ceiling at 0600Z, we would expect the 1200Z ceiling to be below 2,000 feet 31.2% of the time.

4.10 An Example of Calculating Joint-Event Conditional Probability. Single-event conditional probabilities of both ceiling and visibility are necessary to compute the joint conditional probability. Each single-event conditional probability is computed using the procedure outlined in the previous section. Those single-event conditional probabilities are converted to probabilities above the threshold, then used as input to Equation 2.16 to estimate joint conditional probability. Subtracting this value from 1 gives the probability of ceiling, visibility, or both being below the threshold.

To explain further, let's use some information from the previous example. The 0600Z ceiling and visibility are 3,000 feet and 3 miles. Suppose we want to find the joint conditional probability of a 2,000-foot ceiling and/or a 2-mile visibility at 1200Z. We already know that the conditional probability of a 2,000-foot ceiling at 1200Z, given that the 0600Z ceiling was 3,000 feet, is 0.312 or 31.2%. Using the Weibull function and setting p_0 = 0.94, we find that the conditional probability of a 2-mile visibility at 1200Z, given a 0600Z visibility of 3 miles, is 0.150 or 15%. Again, we convert the probabilities to above the threshold, or 0.688 for ceiling and 0.850 for visibility.

Next, we enter these conditional probabilities into Equation 2.16, as shown, to calculate the joint conditional probability. We find the conditional probability of a 2,000-foot ceiling and/or 2-mile visibility at 1200Z to be 0.385 or 38.5%.

$$P\,(C\geq 2000\ ft,\ V\geq 2\ miles|C\geq 3000\ ft,\ V\geq 3\ miles) = 0.7P\,(C_{At}|C_0)\,P\,(V_{At}|V_0) + 0.3MIN\,[P\,(C_{At}|C_0),\ P\,(V_{At}|V_0)]$$

$$= 0.7(0.688)(0.850) + .3(0.688) = 0.615 \tag{2-16}$$

$$(C<2000\,ft\ and/or\ V<2\ miles) = 1 - 0.615 = 0.385$$

4.11 Model Output. Complete examples of MODCV output are provided in Tables 4.3 through 4.6. Ceiling and visibility categories are specified by the user and are printed along the left margin. Times printed along the top designate each time step. Probabilities at each time step will total approximately 100% (±2%) due to rounding errors. *Unconditional* probabilities represent climatological averages; *conditional* probabilities modify them according to the current condition.

4.11.1 ***Unconditional Visibility Probability.*** Table 4.3 gives unconditional visibility probabilities for Ramstein AB, West Germany, during January. The first category is for visibility below 400 meters; probabilities vary from 1-3% throughout the 24-hour time period. The second and succeeding categories represent the interval greater than or equal to 400 meters but less than 800 meters, and so on. The last category represents the interval from greater or equal to 8,000 meters to positive infinity. Categories are cumulative; therefore, there is a 22% probability of a visibility less than 3,200 meters at 07Z. Unconditional probabilities change only when coefficients change to match the proper 3-hour time periods. Note the same probabilities for 06-08Z, 09-11Z, etc. Interestingly, the climatology for 15 and 18Z are similar even though the coefficients are slightly different.

TABLE 4.3. Modeled Visibility Unconditional Climatology, Ramstein AB, January, 0600Z.

Cat Top Meters	07Z	08Z	09Z	10Z	11Z	12Z	15Z	18Z	00Z	06Z
400	2	2	3	3	3	1	1	1	2	2
800	3	3	3	3	3	2	2	2	2	3
1200	3	3	3	3	3	2	2	2	2	3
1600	3	3	3	3	3	3	2	2	2	3
3200	11	11	13	13	13	11	10	10	10	11
4800	10	10	12	12	12	11	10	10	9	10
8000	18	18	20	20	20	21	19	19	16	18
99999	51	51	43	43	43	49	53	53	55	51

4.11.2 ***Unconditional Joint Probability.*** Table 4.4 gives joint unconditional probabilities of ceiling and visibility for McChord AFB, WA, during January. The ceiling and visibility categories are combined (see Paragraphs 2.5 and 4.10) to produce a weighted probability. This table will produce different probabilities than individual ceiling and visibility tables. Once again, note the change of probability with the change of coefficients at 13-14Z and 15-17Z.

TABLE 4.4. Modeled Ceiling/Visibility Unconditional Climatology, Mcchord AFB, January, 1200Z.

Cat Top Feet/Mi	13Z	14Z	15Z	16Z	17Z	18Z	21Z	00Z
200/.25	7	7	6	6	6	5	3	3
500/.5	7	7	7	7	7	7	4	4
1000/1	11	11	12	12	12	12	11	10
1500/1.5	9	9	9	9	9	10	10	10
2000/2	7	7	7	7	7	8	9	8
2500/3	7	7	7	7	7	7	8	9
3000/7	11	11	13	13	13	14	15	18
9999/9999	42	42	39	39	39	36	40	38

4.11.3 ***Conditional Ceiling Probability.*** Table 4.5 shows conditional ceiling probabilities for Ramstein AB during January at 0600Z, given a ceiling of 900 feet. Again, note that the categories are cumulative. The function can be broken into many segments, but they still add up to the whole. For example, at 12Z there is a 35% probability that the ceiling will stay below 1,000 feet. The probability of a ceiling below 3,000 feet but greater or equal to 1,000 feet is 52%. If the first category were 3,000 feet, the probability would be 87%, ± 1% for rounding. Use of conditional probability by a forecaster is subjective. A commonly used technique is to key on the largest probability above or below a certain threshold, then modify it with other data. For example, recent frontal passages or yesterday's timing for improving conditions should be considered. Caution should be exercised depending on how the categories were set up.

TABLE 4.5. Modeled Conditional Climatology, Ceiling 900 feet, Ramstein AB, January, 0600Z.

Cat Top Feet	07Z	08Z	09Z	10Z	11Z	12Z	15Z	18Z
200	0	0	0	0	0	0	0	0
500	1	4	5	6	7	4	3	5
1000	59	50	43	40	37	31	23	22
1500	34	30	29	26	25	25	21	18
2000	6	10	12	13	13	14	14	12
2500	1	3	5	6	7	8	9	9
3000	0	1	3	3	4	5	6	6
99999	0	1	3	6	8	12	22	27

4.11.4 ***Conditional Joint Probability.*** Table 4.6 shows joint conditional probabilities of January ceiling and visibility for McChord AFB at 1200Z. If you compare Table 4.6 with Table 4.4, you'll see how much of a difference the current condition can make. The third category (1,000/1) changes the most at 13Z, increasing from 11% to 46%. Of course, both current conditions fall into this category. If either current condition were in a higher or lower category, the probabilities would change accordingly. The joint table probabilities will be different than the ceiling or visibility conditional tables alone. The joint probabilities will usually be higher in the lower categories since two conditions are used. Another tendency of MODCV's conditional probabilities is to favor the current condition category. In Table 4.5, the third category (1,000 feet) continues to show a high probability (22%) at 18Z. Similarly, in Table 4.6, the category that contained the current condition has the highest probability (18%) at 00Z. Using the highest probabilities is a good first guess, but remember that categories are cumulative--interpret them with respect to the initial conditions.

TABLE 4.6. Modeled Ceiling/Visibility Conditional Climatology, Ceiling 800 Ft/ Visibility .75 Mile, McChord AFB, January, 1200Z

Cat Top Ft/Mi	13Z	14Z	15Z	16Z	17Z	18Z	21Z	00Z
200/.25	9	13	15	15	16	13	7	6
500/.5	22	21	20	19	18	17	10	8
1000/1	46	36	31	28	26	27	23	18
1500/1.5	17	17	17	16	15	16	18	16
2000/2	4	7	8	8	8	9	12	11
2500/3	1	3	4	5	6	6	9	10
3000/7	0	2	3	5	6	7	10	15
9999/9999	0	1	2	4	5	6	13	15

Chapter 5

MODEL VERIFICATION

5.1 General. Eleven stations, selected to allow for verification under different climatological regimes, were used to test MODCV's capabilities; they are:

RAF Mildenhall, UK	Shaw AFB, SC	Ramstein AB, West Germany	McChord AFB, WA
Osan AB, Korea	Clark AB, RP	Shemya AFB, AK	Eglin AFB, FL
Minot AFB, ND	Lajes AB, Azores	Cannon AFB, NM	

MODCV was tested against wind stratified conditional climatology (WSCC). The Brier skill (P) score, which will be discussed in Paragraph 5.2, was used to compare the probability forecasts. The paired t-test (to be discussed in Paragraph 5.3) determined the statistical significance of P-score differences between MODCV and WSCC.

5.2 Brier Skill (P) Score. The P-score takes the form of:

$$P = \frac{1}{N\left[\sum_{j=1}^{r}\sum_{i=1}^{N}(f_{ij} - E_{ij})^2\right]} \tag{5.1}$$

Where r is the number of forecast categories, N is the number of days, f is the probability forecast of the event occurring in that category, and E takes the value of one or zero according to whether the ceiling or visibility occurs in that category. P ranges from 0 (perfect) to 2 (worst). For this test, we used six categories derived from WSCC tables, as shown in Table 5.1.

TABLE 5.1. Brier P-Score Input and Output for RAF Mildenhall.

MODCV Forecast (f)	Verified Category (E)		MODCV Forecast (f)	Verified Category (E)	
0	0	A (0-199 ft)	0	0	A (0-199 ft)
0	0	B (200-499 ft)	0	0	B (200-499 ft)
.02	0	C (500-999 ft)	0	0	C (500-999 ft)
.37	0	D (1,000-2,999 ft)	.01	0	D (1,000-2,999 ft)
.49	0	E (3,000-9,999 ft)	.21	0	E (3,000-9,999 ft)
.12	1	F (≥10,000 ft)	.78	1	F (≥10,000 ft)
----------28			----------25		
0	0	A (0-199 ft)			
0	0	B (200-499 ft)			
.01	0	C (500-999 ft)	....		
.32	1	D (1,000-2,999 ft)			
.52	0	E (3,000-9,999 ft)			
.15	0	F (≥10,000 ft)	0	0	A (0-199 ft)
----------27			0	0	B (200-499 ft)
0	0	A (0-199 ft)	0	0	C (500-999 ft)
0	0	B (200-499 ft)	.02	0	D (1,000-2,999 ft)
0	1	C (500-999 ft)	.26	0	E (3,000-9,999 ft)
.11	0	D (1,000-2,999 ft)	.72	1	F (≥10,000 ft)
.49	0	E (3,000-9,999 ft)	----------1		
.39	0	F (≥10,000 ft)			
----------26			**P = .6852106**		

Verification data was collected during the month of February 1987. Because of the sheer bulk of the data that had to be entered manually, only two forecasts (for 3 and 24 hours) were verified. As an example, Table 5.1 shows Mildenhall's MODCV ceiling probabilities (f) for the six categories and the category observed (E) at the 3-hour point for the Mildenhall afternoon forecast. A skill score of .685 is calculated for the 28 days in February. Skill scores for WSCC and MODCV were computed at all 11 stations and for both verfication times. Table 5.2 shows the skill score for WSCC ceiling (WC) and visibility (WV), and for MODCV ceiling (MC) and visibility (MV). As you can see, Mildenhall's afternoon ceiling 3-hour verification (MC = .69) wasn't as good as WSCC's (WC = .64). But Osan's morning MODCV visibility verified at 24 hours (MV = .28) is better than WSCC's visibility (WV = .42). Clark's data could be misleading, but almost all forecasts were verified correctly in category F. The P-scores show a wide range of results.

TABLE 5.2. Forecast Verification Results (P-Scores) for 11 Stations.

	Morning								Afternoon							
	3 hours				24 hours				3 hours				24 hours			
	WC	MC	WV	MV	WC	MC	WV	MV	WC	MC	WV	MV	WC	MC	WV	MV
RAMSTEIN	.62	.52	.66	.63	.83	.76	.82	.84	.50	.53	.60	.47	.77	.72	.79	.72
MILDENHALL	.53	.60	.26	.45	1.47	.78	.60	.61	.64	.69	.38	.37	.72	.75	.43	.48
CANNON	.22	.41	.29	.29	.42	.55	.38	.43	.25	.38	.12	.12	.21	.48	.25	.26
LAJES	.18	.23	.07	.07	.26	.34	.00	.00	.26	.49	.00	.14	.47	.45	.14	.14
OSAN	.01	.11	.27	.30	.08	.09	.42	.28	.16	.09	.51	.64	.28	.27	.47	.50
MCCHORD	.30	.32	.21	.17	.35	.39	.18	.21	.09	.11	.00	.05	.11	.18	.01	.02
SHEMYA	.40	.42	.26	.27	.69	.66	.47	.46	.52	.51	.35	.33	.56	.62	.55	.48
EGLIN	.21	.31	.20	.27	.51	.45	.29	.27	.30	.23	.25	.18	.49	.53	.33	.32
SHAW	.27	.24	.26	.21	.66	.42	.25	.26	.30	.34	.31	.33	.66	.36	.22	.20
MINOT	.53	.62	.33	.42	.68	.67	.20	.21	.51	.46	.11	.14	.69	.64	.34	.29
CLARK	.00	.00	.01	.00	.o1	.00	.00	.00	.00	.00	.11	.00	.00	.00	.00	.00

5.3 Paired T-test. The paired t-test was used to determine if differences between MODCV and WSCC P-scores were statistically significant. The mean differences ($\bar{d}$) between MODCV and WSCC P scores were calculated from Table 5.2. The following steps were performed:

a. Null Hypothesis: $(H_0): \mu_d = \mu_{MODCV} - \mu_{WSCC} = 0$ (No difference)

b. Alternate: $(H_a): \mu_d \neq 0$ (Some difference)

c. Test Statistic: $|t| = \dfrac{\bar{d} - 0}{s_d/\sqrt{n}}$, where $\bar{d}$ and s_d are the mean and standard deviation of the n differences.

d. Rejection Region: With 87 degrees of freedom, we reject H_0 if $|t| > t_{.05/2}$. Therefore, $P(|t| \geq c) = \alpha$, which is equal to the probability of rejecting H_0 when it is indeed true.

e. Conclusion: For this analysis, $\alpha/2 = 0.025$ gives a critical value $c = 1.99$. It follows, then, that to reject the null hypothesis (H_0) of no difference, our calculated $|t|$ must be ≥ 1.99. Substituting the appropriate values into our test statistic we find:

$$|t| = \frac{-2.70 \cdot 10^{-3} - 0}{0.112/\sqrt{(88)}} = 0.226$$

At the 0.05 significance level, $|t| = 0.226$ is not greater than or equal to 1.99. We therefore failed to reject the null hypothesis and conclude that there is no statistical significant difference between the P-scores for the WSCC forecasts and the P-scores for the MODCV forecasts. MODCV shows good skill when compared to WSCC tables. Although these results are based on the verification of only 11 stations for the month of February 1987, the results are similar to those found in a test conducted by AFGWC (Globokar, 1978). Modeling, therefore, offers a viable alternative for representing climatologies of ceiling and visibility.

Chapter 6

SUMMARY AND CONCLUSIONS

MODCV was created to make available climatology easier to use. This user-friendly program provides an entire year's ceiling and visiblity probabilities for various stations at the touch of a button. It replaces the considerable bulk of the WSCC and RUSSWO, as well. Climatology for dozens of stations can now be simply and easily maintained for planning, mobility, and similar applications.

This electronic convenience, however, is not without the expense of some accuracy. Modeling of CDFs with the Weibull curves, for example, introduces a 3-6% error. But compared to the benefits, this error is minimal. Modeling also produces a continuous curve that can account for extremes that haven't occurred and for thresholds that aren't commonly recorded (3,300-foot ceilings, for example).

Unconditional climatological probabilities can be calculated as the area under the curve for that station and time period. Conditional probabilities can then be computed using the Ornstein-Uhlenbeck equation, a first-order Markov process. The Markov process gives a future value of a given weather variable using its current state and a serial correlation. The methodology in MODCV requires that the weather variables be converted to an equivalent normal form. This is accomplished through transnormalization, which simplifies the mathematics. The algorithms then produce unconditional and conditional climatological probabilities from the same database.

Although theory indicated that the program described in this report was valid, the output needed verification. A 1-month study (documented here) was conducted to compare MODCV to the acceptable WSCC. Brier scores were shown to be statistically the same , indicating that MODCV is practical for operational use.

DISTRIBUTION

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Federal Coordinator for Meteorology, Suite 300, 11426 Rockville Pike, Rockville, MD 20852 1
AFGL Library, Attn: SULLR, Stop 29, Hanscom AFB, MA 01731-5000 1
Atmospheric Sciences Laboratory, Attn: SLCAS-AT-AB, Aberdeen Proving Grounds, MD 21005-5001 1
Atmospheric Sciences Laboratory, White Sands Missile Range, NM 88002-5501 1
U.S. Army Missile Command, ATTN: AMSMI-RD-TE-T, Redstone Arsenal, AL 35898-5250 1
Technical Library, Dugway Proving Ground, Dugway, UT 84022-5000 1
NCDC Library (D542X2), Federal Building, Asheville, NC 28801-2723 1
DTIC-FDAC, Cameron Station, Alexandria, VA 22304-6145 2
NIST Pubs Production, Rm A-405, Admin Bldg, Gaithersburg, MD 20899 1
ANG Weather Flights (through AWS/RF) 40
75th Ranger Btn (Attn: Lt David Musick), Ft Benning GA 31905-5000 1
HQ 5th U.S. Army, AFKB-OP (SWO), Ft Sam Houston, TX 78234-7000 1
CNVEO/DN, ASL MET Team, Ft Belvoir, VA 22060-5677 1
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AWSTL, Scott AFB, IL 62225-5438 125